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Weighted Visibility Graph With Complex Network Features in the Detection of Epilepsy

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ABSTRACT Epilepsy detection from electrical characteristics of EEG signals obtained from the brain of undergone subject is a challenge task for both research and neurologist due to the non-stationary and chaotic nature of EEG signals. As epileptic EEG signals contain huge fluctuating information about the functional behavior of the brain, it is hard to distinguish the fundamental dynamic, complex network of EEG signals without considering the strength among the nodes as they are connected with each other on the basis of these strengths. The prior research on natural visibility graph did not consider this issue in epileptic seizure, although it is a very important key point to have representative information from the signals. Hence, this paper aims to introduce a new idea for epilepsy detection using complex network statistical properties by measuring different strengths of the edges in natural visibility graph theory, which is considered as weight. Thus, the proposed method is named ''weighted visibility graph''. In this proposed method, first, the epileptic EEG signals are transformed into complex network and then two important statistical properties of a network such as modularity and average weighted degree used for extracting the imperative characteristics from a network of EEG signals. After that, the extracted features are evaluated by two modern machine-learning classifiers such as, support vector machine with a different kernel function and k-nearest neighbor. The experimental results demonstrate that the combined effect of both features is valuable for network metrics to characterize the EEG time series signals in case of weighted complex network generating up to 100% classification accuracy.

INDEX TERMS Average weighted degree, complex network, EEG, Epilepsy, KNN, modularity, SVM, visibility graph, and weighted visibility graph.

I. INTRODUCTION

Epilepsy is the most common chronic neurological syndrome after Alzheimer's disease and stroke in the world. According to World Wide Web, around 50 million people worldwide has epilepsy and is suffering with this recurring and unpredictable seizure disorder [1]. The main root of Epileptic seizure is disproportionate, synchronized activity of vast groups of neurons in the brain. Epileptic syndrome leads to range of short-term alterations in cognition and behavior [2]. Moreover, Epileptic patient always having mental stress and anxiety that accompanies untimely seizure attacks. For the anti-seizure medication, it is valuable to detect epilepsy syndrome as it gives information about the underlying etiology. EEG is one of the main bio-marker that can measure voltage fluctuations of the brain and EEG data analysis helps to investigate the patient with epilepsy syndrome as epilepsy leaves their signature in EEG signals. As EEG data are in time series form, therefore epilepsy detection is mostly done by using time series analysis techniques ranging from linear methods to non-linear methods. Linear methods to analyze time series data comprise time-frequency analysis, i.e. from Fourier transformation to wavelet transformation [3]–[5]. Non-linear methods include the calculation of Lyapunov exponents, entropy and co-relation dimensions [6]–[8]. However, these methods are not able to perpetuate all characteristics of EEG time series data such as, non-stationary, chaotic nature [10]. Henceforth, there is continuous research towards the development of new techniques that can detect epilepsy syndrome by preserving the relevant as well as important information and further more provide additional information about epileptic EEG signals. As EEG signals are non-linear and chaotic in nature, traditional linear methods are not sufficient to represent epileptic EEG data [9]–[11]. This motivates us to use a complex network technique for the detection of epilepsy disorder.

In 2006, Zhang and Small [13] introduced the concept of mapping time series to complex network and discovered that complex network is an alternative approach to visualize the underlying hidden patterns of the time series. The presence of different behavior (chaotic or fractal) of time series can be distinguished by using different network measurements, as the statistical properties of the network could be utilized to obtain the information present in the time series. In the current era, complex network and graph theory approach is becoming the emergent field to detect various brain disorders [14]. The complex network approach introduces a new direction in the neuroscience field to detect brain abnormalities by investigating the changes in the characteristic properties of the EEG complex network. The presence of multiple behavior of time series is distinguished by using different network attributes because different time series exhibit different statistical features.

In 2008, Lucas *et al.* [15], introduced a visibility graph to map time series data into complex network and demonstrate that visibility graph can inherit several non-linear characteristics of time series. In 2010, first time visibility graph algorithm applied by Ahmadlou *et al.* [16], for the detection of brain disorder named as Alzheimer syndrome and they obtained very promising results. Afterward, many researchers and clinicians for the detection of epilepsy disorder [17], [18] have used this visibility graph algorithm, but their proposed approaches have some limits as they have not considered an important fact that in network, the links exhibit different strengths and all the nodes of the network are connected with each other based on this strength. Zhu *et al.* [19] has introduced the concept of weight in the complex network to detect epilepsy, but they have implemented this on the horizontal visibility graph, which is a subgraph of visibility graph. Also, they did not clearly mention on which criteria they used an edge weight function and how it helps to detect the sudden fluctuation in epileptic EEG signals. Therefore, addressing the limitation of the existing methods, we develop an algorithm considering a new edge weight for the natural visibility graph in the complex network.

In this study, we introduce a novel method in the detection of epileptic EEG signal to determine a weight of the edge between the two nodes by means of radian function, which is clearly described in Section II (B). The reason behind selecting the action as an edge weight function is also discussed in that section. After transformation of EEG signals into the weighted visibility graph, two important characteristics of a network: modularity and the average weighted degree are extracted from the weighted visibility graph as features. The reason of considering these two features as they are very prominent to provide the valuable information about the time series acquired by analysis of the structural pattern of complex networks. Finally, the extracted feature set is tested by two popular machine learning techniques: SVM and KNN. In our previous research [20], we developed different edge weight method in the complex network for detection of epilepsy syndrome. In that methodology, we considered the directional nature of the observations as an edge weight for the visibility graph in the complex network. We extracted only one feature: average weighted degree of the complex network of the weighted visibility graph in that method [20], which sometimes may not convey all of the important information of the complex network. The experimental evaluation of that method was performed only one case study: Set A vs Set E from Bonn University data (see description in Section II (A)). Dealing the issues, this study explores an enhanced method for epileptic seizure detection method which is evaluated by four case studies as discussed in Section III. The experimental results prove the consistency of the proposed method in this paper. To the best of our knowledge, the edge weight concept in a visibility graph with the modularity and average weighted degree is totally new in the epilepsy detection and has not been used before.

Epileptic EEG data are nonlinear in nature and this nonlinear nature exhibit multi-fractal behavior [21]. Detection of epilepsy abnormality from the complex network of EEG signals can be possible by retrieving comprehensive information from their structure. The most promising method is to decompose the EEG networks into groups of highly interlinked nodes named as clusters and used a proper function, which helps to discriminate between different kinds of EEG signals. Modularity and average weighted degree are the most promising feature for this purpose. In this study, we introduce a novel technique to detect epilepsy by mapping EEG signal into weighted network named as a weighted visibility graph (WVG). Then two statistical properties of network named as modularity and average weighted degree of the network are extracted as features and classification experiment are performed on different EEG data set by using two most popular machine learning classifiers named as, SVM and KNN. The experimental results are quite promising with 100% accuracy in the classification of EEG signals of epileptic seizure activity set (E) and healthy person with eyes open (A). Moreover, the results for other classification test cases also suggest that our proposed technique is best appropriate to differentiate between different kinds of EEG signals.

This remaining paper has been structured as: Section 2 presents the complete description of the data set used in the experimental part along with the proposed methodology. Section 3 comprises the detailed discussion about the experimental procedure and the results. Conclusions along with the future work are stated in section 4.

II. MATERIAL AND METHOD

The flow chart of the proposed methodology is shown in Fig. 1. The dataset and the different steps of the methodology has been discussed below.

A. DATASET

In this paper, we have analyzed the online available EEG repository of epilepsy data that has been developed and issued by the department of epilepsy in Bonn university, (http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3) Germany. The complete EEG database comprises of five sets denoted as A, B, C, D and E. Each

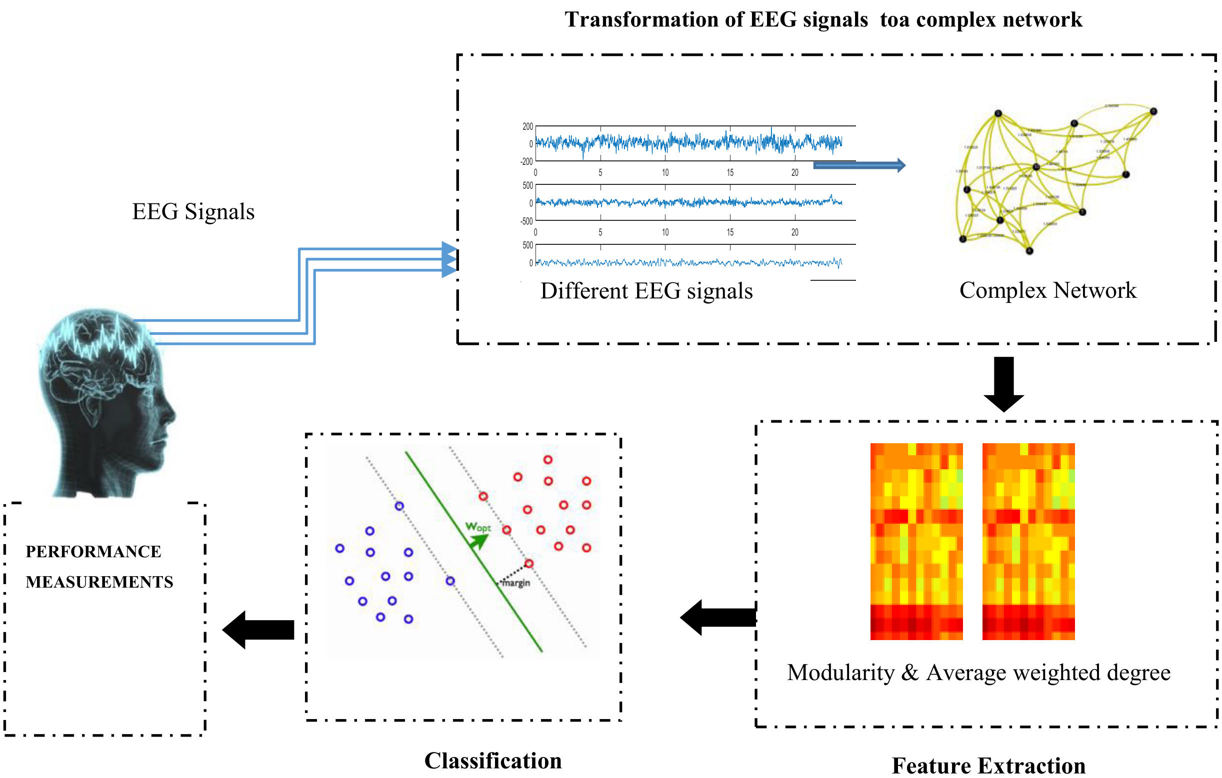

FIGURE 1. Schematic flow chart of the proposed methodology.

set contains 100 single channel EEG signals of 23.6s from five separate classes. For the recording of EEG signals the 10-20 system of electrode placement is used. All EEG recordings were made with the same 128-channel amplifier system, using an average common reference. The recorded data were digitized at 173.61 samples per second using 12-bit resolution. The band-pass filter setting is 0.53 Hz to 85 Hz. In this research study, we have used all the five data set to evaluate the performance of our proposed methodology. The detail explanation of this database is available in Andrezejak *et al.* [22]. Each channel EEG signal has 4097 sample data points. However, in order to reduce the computation time we had segmented the each channel with 1024 data sample points per segment.

Fig. 2 illustrates the example of EEG signals from each channel of five sets (A to E). The brief description of the data set has been described below:

- Set A: The surface EEG recorded of five healthy volunteers with their eyes open.
- Set B: The surface EEG recorded of five healthy volunteers with their eyes closed.
- Set C: The intracranial recording in seizure free interval during the hippocampal formation of the opposite hemisphere of the brain of patient.
- Set D: The intracranial recording of epileptogenic zone of epileptic patient in seizure free interval.
- Set E: The dataset is recorded during seizure activity, i.e. ictal period.

In this research study, we used the above-mentioned data sets to evaluate the performance of the proposed technique by defining four different groups of problems (test cases) as described in Table III of results and discussion section.

B. TRANSFORMATION OF TIME SERIES EEG SIGNALS TO COMPLEX NETWORK

Complex network theory is a branch of complexity science, which deal with graph theory, statistical physics and data analysis. Nowadays it is becoming an emerging technique in the field of quantitative analysis of long-range dependency and fractality of time series data. As this branch provides several methods to study the underlying dynamics of time series data. Visibility graph is one of the method among them. The Visibility Graph (VG) technique has the property to characterize the time series in terms of graph theory as it can inherit the dynamical properties of the time series data from which it was created. The resulting network can be used to acquire the valuable information about the time series. According to Liu *et al.* [23] VG is robust to noise and not stimulated by the selection of choice of some parameters (threshold value ε as like in TSCN [24] and recurrence network). The literature study also reveals that the topological invariant of visibility graph is closely allied to the underlying EEG time series data. Therefore, it is efficient to distinguish the different underlying dynamical edifices in the EEG recording of healthy and epileptic patient. That is the main motive of using the natural visibility graph in the analysis of EEG signal

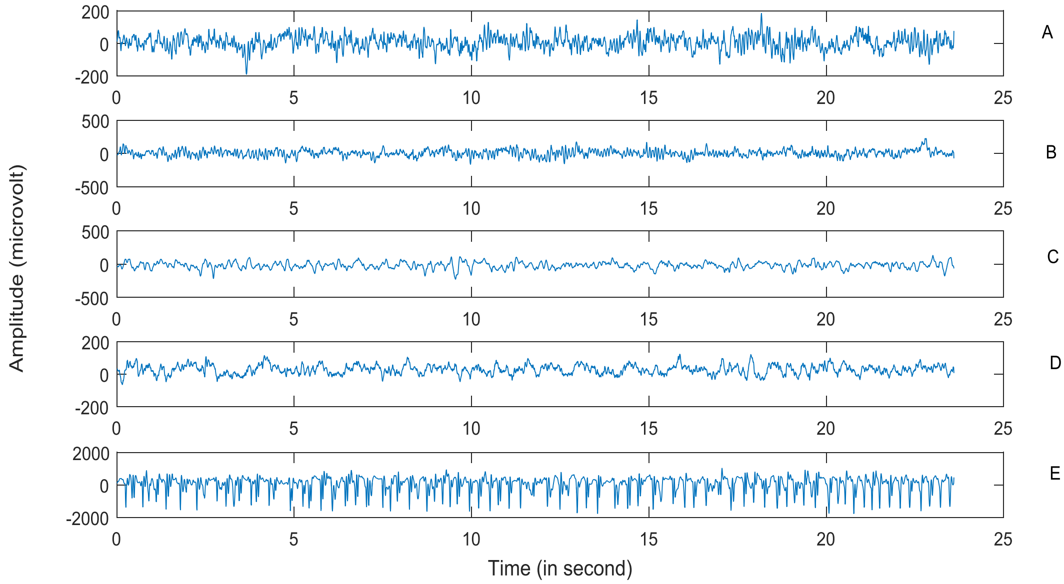

FIGURE 2. Example of single channel of EEG time series data of five subsets (A, B, C, D and E).

in this paper for edge detection. In this paper EEG time series data are transformed to weighted visibility graph. We used the following steps to construct the weighted visibility graph with the help of the natural visibility graph.

1) STEP I (CONSIDERED EACH DATA SAMPLE POINTS OF TIME SERIES DATA AS THE NODES OF THE GRAPH)

For the construction of a Weighted Visibility Graph (WVG) of EEG time series data, consider G=(N,E) be a graph where N=$\{n_i\}, i = 1, 2, \ldots\ldots$.N, are the nodes and E $= e_i$, $i = 1, 2, 3, \ldots\ldots\ldots\ldots$N, are the edges of the graph. A time series $x(t_i), i = 1, 2, \ldots\ldots.N$ of N sampling points and node n_i correspond to data sample point x_i.

2) STEP II (THE EDGES (LINK) BETWEEN THE NODES OF THE WEIGHTED VISIBILITY GRAPH ARE BUILT UPON THE NATURAL VISIBILITY GRAPH EQUATION)

In order to find the links between different nodes of the weighted visibility graph, we used the natural visibility graph algorithm which was developed by L. La Caesar *et al.*, in 2008 [15]. The visibility graph is based upon the concept of Euclidean plane where each vertex represents the point's location and the links between the associated nodes is only possible if there is visibility between them. According to VG method, the edges between any two pair of nodes exits only, if they satisfied the following rule:

$$x(t_c) < x(t_a) + (x(t_b) - x(t_a))\frac{t_c - t_a}{t_b - t_a}, \quad a < c < b \quad (1)$$

Where, $x_a = x(t_a)$ and $x_b = x(t_a)_{are}$ the data sample points and t_a and t_b are any two arbitrary time events and t_c is any event exits between them i.e. $t_a < t_c < t_b$. Fig. 3 illustrates the VG of time series data that represent the edge construction based on visibility among them

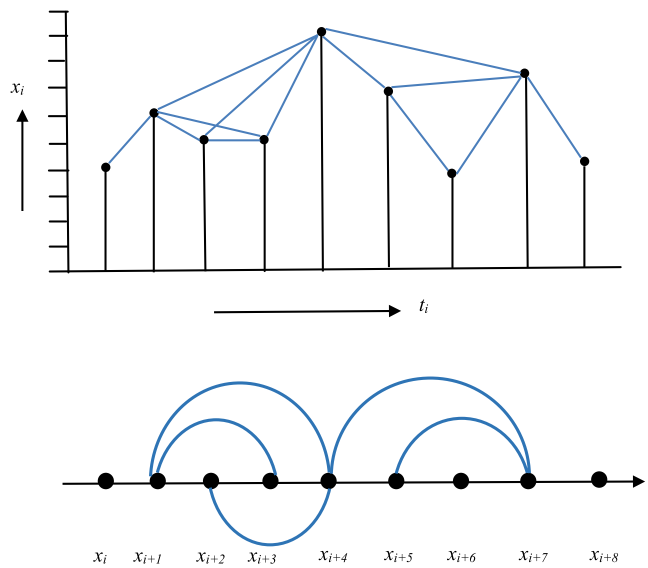

FIGURE 3. Visibility Graph.

3) STEP III (DETERMINE THE EDGE WEIGHT BETWEEN TWO NODES)

Literature studies in the field of network theory have exposed that more robust result of complex network can be obtained by preserving weight information in it [25] as compared to binary network (which just only gives information about the links either exits between two nodes or not). Because weighted complex network plays a significant role to distinguish between weak and potentially less important edges (links) as different edges have different strength. In this paper EEG time series data are described by constructing a weighted visibility graph. Weight is a value that is associated with the edge of a graph. Weighted graph can be represented as a triple G (V, E, w) where w: E→R weighted function.

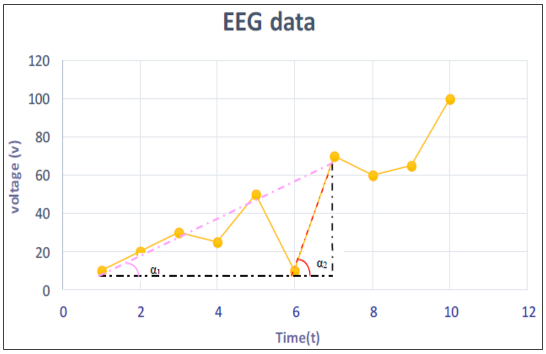

FIGURE 4. Example to represent the edge weights between different data points.

In this paper, all the edges of the graph are directional in nature as a link between node $n_a = x_a$ and node $n_b = x_b$ is considered to have direction from n_a to node n_b where $a < b$. In this paper, the absolute value of edge weight has been considered. The edge weight is calculated by equation 2.

$$w_{ab} = \arctan \frac{x(t_b) - x(t_a)}{t_b - t_a}, \quad a < b \tag{2}$$

Where, w_{ab} represents the weight of the edge between node n_a and node n_b and in this paper we have considered all the edge weight value in radian function. The arctan is arc tangent which is an inverse trigonometric function that helps to detect the sudden change in the EEG signals. We clearly explain the advantage of the above edge weight in EEG data analysis in Example 1: Afterwards the following simple Example 2 illustrates how edge weight is calculated with the help of equation 2.

Example 1: Let's consider an EEG time series X = {10, 20, 30, 25, 50, 10, 70, 60, 65, 100} with associated time t = {1, 2, 3, 4, 5, 6, 7, 8, 9, 10}. As it is clear from the Fig. 4 that x (t_1) = 10 and x (t_6) = 10 i.e. both are having the same value and also there is a sudden fluctuation at $x(t_7) = 70$. The angle between $x(t_1)$ and $x(t_7)$ is α_1 and α_2 is the angle between $x(t_6)$ $x(t_7)$. According to the equation 2 the edge weight between $x(t_1)$ and $x(t_7)$ is:

$$w_{17} = \arctan \frac{70 - 10}{7 - 1} = 1.471 = \alpha_1$$

Similarly the edge weight is calculated between $x(t_7)$ and $x(t_8)$ which is:

$$w_{67} = \arctan \frac{70 - 10}{7 - 6} = 1.554 = \alpha_2$$

Thus the above example clearly states that even though the two nodes (data sample points) are having same values, but their strength to connect with third node will vary account of their edge weight. Also with the fluctuating values of EEG signals, the edge weights will also vary which helps to discriminate between different kinds of EEG signals.

Example 2: Table I represents the EEG time series data with their corresponding nodes and data sample point values. The edge between the nodes is determined with the help of equation 1. Then the edge weight between different nodes are calculated by using equation 2. The Table II represents the edge between the nodes and weight values associated with the edges of EEG time series data of Table I. In Table II, E_{12} represents the edge between node 1 and node 2 and $w_{12} = 1.529$ represent the weight value associated with this edge.

TABLE 1. Representation of Eeg Time Series with their corresponding Nodes, Data Sample Points and Edges

Time Series Data	Data Points	Time	Nodes
x_1	100	t_1	1
x_2	124	t_2	2
x_3	153	t_3	3
x_4	185	t_4	4
x_5	210	t_5	5
x_6	220	t_6	6
x_7	216	t_7	7
x_8	222	t_8	8
x_9	240	t_9	9
X_{10}	265	t_{10}	10

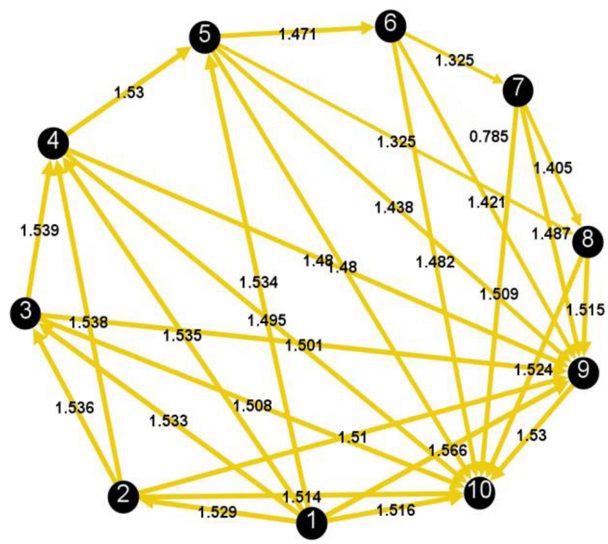

FIGURE 5. Weighted Visibility Graph.

4) STEP IV (CONSTRUCTION OF WEIGHTED VISIBILITY GRAPH(WVG))

Finally weighted visibility graph is constructed by using the edge weight value calculated in the last step. Fig. 5 represents the weighted visibility graph which is constructed on the basis of data available in Table I and Table II.

C. FEATURE EXTRACTION

Feature extraction is a significant part for classification of EEG signal data. Technically, a feature represents the distinctive property and an identifiable measurement obtained from a segment of a pattern.

The feature extraction process compresses the large volume EEG data into relevant and important feature vector set

TABLE 2. Example of edges and weight between different nodes of eeg time series data of tab.

Edges	Weight (w)	Edges	Weight (w)	Edges	Weight (w)
E_{12}	1.529	E_{13}	1.533	E_{19}	1.566
E_{14}	1.535	E_{15}	1.534	$E_{1\ 10}$	1.516
E_{23}	1.536	E_{24}	1.538	E_{29}	1.510
$E_{2\ 10}$	1.514				
E_{34}	1.539	E_{39}	1.501	$E_{3\ 10}$	1.508
E_{45}	1.530	E_{49}	1.480	$E_{4\ 10}$	1.495
E_{56}	1.471	E_{58}	1.325	E_{59}	1.438
$E_{5\ 10}$	1.480				
E_{67}	1.325	E_{68}	0.785	E_{69}	1.421
$E_{6\ 10}$	1.482				
E_{78}	1.405	E_{79}	1.487	$E_{7\ 10}$	1.509
E_{89}	1.515	$E_{8\ 10}$	1.524		
$E_{9\ 10}$	1.530				

at the cost of minimum loss of information. Therefore, it helps in analysis (classification) process by making it more easily and fast in computational speed. In this paper, we have extracted two statistical properties of network named as modularity and the average weighted degree of network as features from the weighted visibility graph as these features are able to focus on how the valuable information about the time series can be acquired by analysis the structural pattern of complex networks. We have introduced modularity feature in the weighted visibility graph to help in distinguishing between various types of EEG signals by detecting communities among their complex network.

The average weighted degree is the second introduced features as it is clear from the section II that because of fluctuations in the epileptic EEG signals the edge weight will show a discrepancy and different kinds of EEG signals exhibit different edge weight among their nodes and thus their resultant networks has a different average weighted degree values.

1) MODULARITY

In a complex network, the modularity concept was introduced by Newman [26]. Modularity is a quality function instead of a method to discover modules (communities). Modularity is a measurement of the quality of partition of the network into clusters (communities). According to Newman if G is a weighted network and A is the weighted adjacency matrix of that network then the *modularity Q* is defined as:

$$Q = \frac{1}{2m}\sum_{i,j}\left(A_{i,j} - \frac{k_i k_j}{2m}\right)\delta\left(C_i, C_j\right) \tag{3}$$

Where $A_{i,j}$ symbolize the weight of the links(edge) between node i; m=1/2 $\sum_{ij} A_{ij}$ represent the total number of links in the network, $k_i = \sum_j A_{i,j}$ is the weighted degree of the vertex i, C_i is the cluster name to which vertex i belongs to, $\delta(C_i,C_j)$ is 1 if both nodes i and node j belongs to the same cluster otherwise $\delta(C_i,C_j)$ is equal to 0. In this paper,we have used *the Louvain method* [27] for modularity calculation of the complex network of EEG signals because it is an easy and efficient method extensively used in the field of community detection from vast complex network. Louvain method is comprised of two parts. Using optimization of modularity in the local manner, the small communities are identified first. In the second part, the nodes belong to the same community are grouped together to rebuild the new network with vertices of the graph are the communities. These two steps will iteratively repeat until the highest value of modularity is accomplished (i.e. There is no increase in modularity value via integration of two communities). When community a combined into community b, then, according to *Louvain* [27] the modularity gain is:

$$\Delta Q_{ab} = \left[\frac{\sum_{bn} + k_{a,bn}}{2m} - \left(\frac{\sum_{tot} + k_a}{2m}\right)^2\right] - \left[\frac{\sum_{bn}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - \left(\frac{k_a}{2m}\right)^2\right] \tag{4}$$

Where, $\sum_{bn}$ represent the total weights of the links that comes under community b; $\sum_{\text{tot}}$ is the total weights of the links that are incident to the vertices in the community; $k_{a,bn}$ is the total weights of the edges from the community a to community b; k_a is the total weights of the edges incident to node a; m is the total weight of all the edges in the network.

2) AVERAGE WEIGHTED DEGREE

The average weighted degree of the network as described above is the second extracted feature of the weighted visibility graph. If a $A_{N\times N} = \{a_{ij}\}$ is an adjacency matrix with N number of nodes is used to represent the weighted visibility graph, then $a_{ij} = 1$ if there is an edge from node i to j

otherwise it's 0. According to [28] the weighted degree of the node i is the total weights of all the edges attached to node i which is represented by:

$$wd_i = \sum_{j\varepsilon B(i)} w_{ij} \tag{5}$$

Where $B(i)$ signifies the neighborhood of node i and w_{ij} represents the weight of the edges between nodes i and j. And the average weighted degree of the network is the average mean of the total weights of the incident links on all the vertices in the network [1].

D. CLASSIFICATION

The classification technique helps to discriminate the unknown testing set of observations into their appropriate classes on the basis of the training set of known observations. A classification technique used a mathematical function named as a classifier to predict the right class of unknown observation of testing data set. In this paper, we have used two well-known supervised machine learning classification method named as Support Vector Machine (SVM) classifier and KNN classifier for the evaluation of the performance of the proposed technique by utilizing the resulting features extracted from feature extraction technique

1) SUPPORT VECTOR MACHINE (SVM)

Currently SVM is a powerful classifier in the field of biomedical science for the detection of abnormalities from biomedical signals. SVM is an efficient classifier to classify two different sets of observations into their relevant class. It is capable to handle high dimensional and non-linear data excellently. On the basis of the structure of training data sets, it helps to predict the important characteristics of unknown testing data. As in this paper, to evaluate the performance of the proposed technique we are having four test cases with two different sets of class so we preferred this classifier for better accuracy results. SVM mechanism is based upon finding the best hyperplane that separates the data of two different classes of category. It is enriched with the property of having different sets of kernel function for the classification of different types of data. The working description of SVM classifier and additional information about different kernel functions are details discussed in [29]. In this paper, we have used the following three different kernel functions of SVM Classifier to analyze the performance of different test cases problems.

1) Linear kernel function:

$$K(x, y) = x^T y \tag{6}$$

2) Polynomial kernel function with degree d:

$$K(x, y) = \left(x^T y + 1\right)^d \tag{7}$$

3) Radial basis kernel function with width σ:

$$K(x, y) = e^{\left(\frac{(-\|x-y\|)^2}{2\sigma^2}\right)} \tag{8}$$

TABLE 3. The classification description of different groups of problem along with their eeg data sets.

Test case	Data Group	Classification Problem Description
Test I	Set A vs Set E	Heathy persons with eye open vs Epileptic patients during seizure activity
Test II	Set B vs Set E	Heathy persons with eye close vs Epileptic patients during seizure activity
Test III	Set C vs Set E	Hippocampal seizure free vs Epileptic patients during seizure activity
Test IV	Set D vs Set E	Epileptic seizure free vs Epileptic patients during seizure activity

Where, $K(x, y)$ is termed as the kernel function, which is built upon the dot product of two invariant x and y.

2) K-NEAREST NEIGHBOR (KNN)

The second classifier used for the classification of different test cases of EEG signals is the K-Nearest Neighbor (KNN) classifier as it is simple and robust to even noisy and large training data set. It is also adaptive in nature because of using local information for prediction of unknown data. It performs the classification task on the basis of frequent class of its nearest neighbors in the feature space [30]. There are several metrics to define the distance in KNN algorithm, but in this paper, we had used the Euclidean distance. If s is the training set and y is the unknown test data, then KNN method will obtain the K nearest neighbors from the s by using the following Euclidean distance between s and y i.e.

$$D(x_y, s) = \sqrt{\sum_{i=1}^{n} (s_i - x_y)^2} \tag{9}$$

E. PERFORMANCE EVALUATION MEASUREMENTS

In this paper the set A, B, C and D are considered as positive class and set E is considered as the negative class respectively. In order to evaluate the classification performance for different test cases in this paper, we have used the following measures parameters in (10)–(12), as shown at the bottom of the next page where, True Positive stands for correctly identified non-seizure activity, True Negative is the correctly identified seizure activity, False Positive is the false identification of non-seizure activity, and False Negative is the falsely recognized seizure activity.

III. RESULTS AND DISCUSSION

In order to examine the validation of the proposed research work, the proposed method is implemented on the benchmark data: Bonn university epileptic EEG data.

The proposed technique is tested on the four different groups of problems (test cases) as described in Table III.

Two classification algorithms named as SVM with different kernel functions and KNN classifier using Euclidean distance have been implemented using MATLAB R2015b

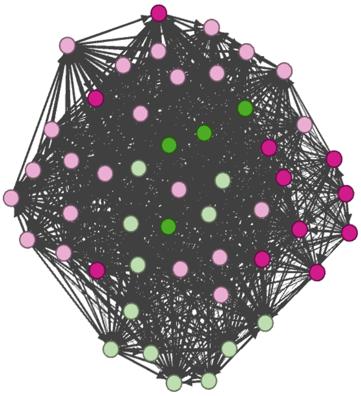

FIGURE 6. A Weighted visibility graph of healthy person with eyes open (set A).

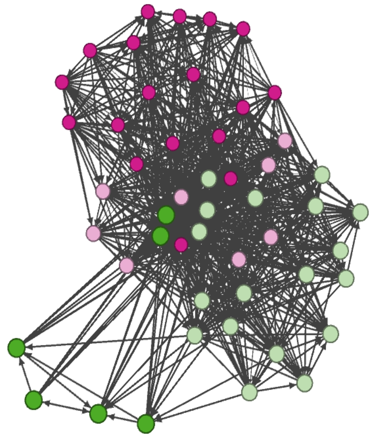

FIGURE 7. A Weighted visibility graph of epileptic seizure activity (set E).

(version 8.6, 64 bits). As each channel of every set contains 4097 data sample points for 23.6 seconds. According to Tang *et al.* [17], there is no significance to use a large number of observations for the conversion of time series EEG data into complex network as the quantification of complexity and self- similar nature of a graph does not need many nodes. In order to include more data, the segmentation of a signal provides more information that is meaningful and can be considered as a part of the entire data set [17]. Moreover, from our previous research [1] we have also investigated that there is not much difference in the accuracy performance when considering segmented and non-segmented approach of EEG signals. In addition, the segmentation of EEG signal makes the computation faster. By considering this information into account, we divided each channel into four segments, i.e. Seg1=1024, Seg2=1024, Seg3=1024, Seg4=1025 data sample points and segmentation is done on the basis of a particular time period i.e. each segment contains the data for 5.9 Sec. Then these four segments are further used as a four independent samples.

As in each data subset, there are 100 channel data with 4097 data points, therefore after segmentation; we have 400 segments with 1024 data sample points. According to the proposed methodology, firstly each segment is converted into a weighted visibility graph. As Fig. 6 and Fig. 7 represents the example of visualization of the weighted visibility graph by using 50 data sample points for single segment of set A (healthy patient with eyes open) and set E (seizure activity) and also clearly demonstrate the difference in the topological structure of both the weighted visibility graphs, where the different colors of nodes represents different groups of modules on the basis of modularity. The main motive behind the consideration of edge weight in visibility graph is to detect the sudden fluctuation occurs during Epileptic seizure attacks.

During the epileptic seizure activity, the amplitude of EEG signals, displays immense fluctuations and our proposed edge weight based algorithm helps to discover this sudden fluctuation for detection of epileptic syndrome because the complex network with seizure activity exhibit different edge weight value which further affect their statistical attributes (features).

For feature extraction part, we have used two statistical properties of complex network named as modularity and average weighted degree. Fig. 8 represent the box plot diagram of the modularity feature set of all the 400 segments of each set A, B, C, D and E with N=1024 per segment. A clear significant difference in the values of the feature set of all the different EEG data set is shown in this Fig.8. Therefore, it is clear from the figure that set E has lowest modularity values as compared to other sets (Set A, B, C and D). According to Blondel *et al.* [27], the modularity value of complex network lies between [−1,1] and the closer is the value of modularity to 1, the stronger is the community structure i.e. the better is the partition of the network. Moreover, according to community structure criteria, Fig. 8 also characterized that Set A, B, C and D has dense connections among the nodes inside the modules as compared to Set E. Similarly Fig. 9 represent the box plot diagram of second extracted feature named as average weighted degree with 400 segments of each set (A, B, C, D and E) and N=1024 per segment.

As it is clearly visible from Fig. 9 that the average weighted degree of Set E has the highest value as compared to other

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{10}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative+False Positive}} \tag{11}$$

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{True Positive+False Negative+True Negative+False Positive}} \tag{12}$$

TABLE 4. The Performance Classification of different test cases of EEG data set with SVM Linear Kernel function Classifier by using each Features Individually as well as by Combining these two features.

Data Group	Performance for modularity features set of WVG			Performance for average weighted degree features set of WVG			Performance for combined feature vector set of WVG		
	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Set A vs E	100	99	99.5	100	100	100	100	100	100
Set B vs E	100	93.45	96.5	89.28	100	94	99.46	93.86	96.5
Set C vs E	98	98.49	98.25	80.64	100	88	98.5	98.5	98.5
Set D vs E	93.33	91.66	92.5	85.47	100	91.5	92.3	90.24	91.25

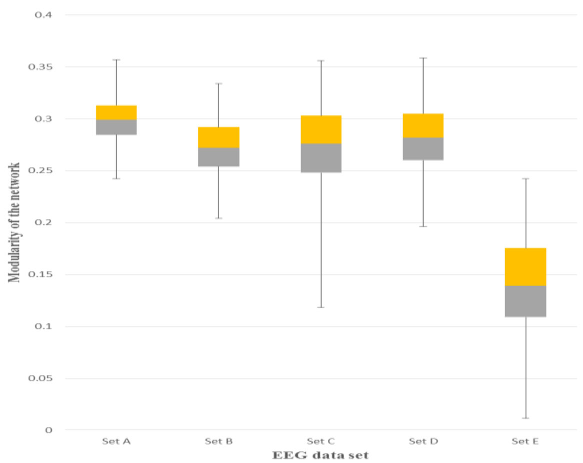

FIGURE 8. Boxplot of the modularity features set of different sets of EEG signals.

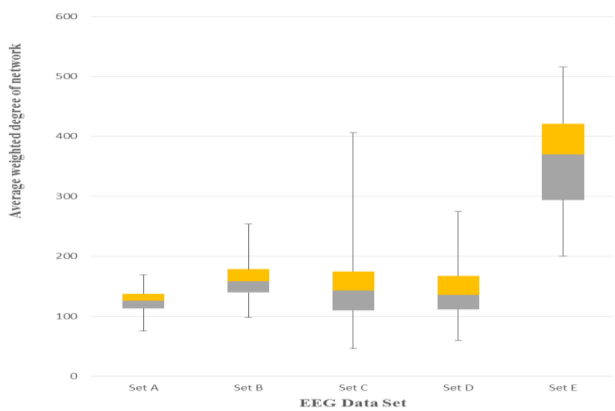

FIGURE 9. Boxplot of the average weighted degree features set of different sets of EEG signals.

Set A, B, C and D. Hence the above analysis results divulge that these two combined feature vectors set are able to imitate the characteristic disparity of different kind of EEG signals. And also one of the important reasons of achieving higher accuracy results for different test cases.

Table IV lists the experiments for the classification results of all the four test cases by using each of the two features separately and also by combining these two features. Firstly the experiment for the classification was performed for all the test cases with each feature set separately. Then tested for the two combined features using SVM with linear kernel function. Table IV clearly displays that average weighted degree feature provides 100% accuracy for test case I whereas modularity feature provide more improved classification results on the remaining three test cases. Thus to acquire overall better-quality results for all the four test cases, these two feature vectors are combined and again SVM classifier with linear kernel function applied.

The results, for each individual feature and their combination demonstrates that the classification performance increased by combining these two features. As shown in Table IV, the combined feature set yield 100% accuracy for test case I, 96.5% for test case II, 98.5% in test case III and 91.25% in test case IV. Therefore, by taking this information into account, the remaining experiments of this paper performed by combining these two features.

As different kernel functions of the SVM classifier plays different role in the classification. Thus, in order to evaluate the classification performance of these features set, we applied additional SVM with RBF kernel function and SVM with polynomial kernel function. Table V represents the classification performance of these two kernel functions of SVM. The Table V clearly demonstrates that SVM classifier with polynomial kernel function has a better overall accuracy as compared to RBF kernel function and linear kernel function.

Furthermore, in order to explore the performance of the proposed technique, we applied another machine learning, supervised classification method named as KNN for different test cases. Different values of K has been experimented on the combined feature vector set and it was investigated that for K=3 and K=10, KNN provides more significant results for all the test cases. Table VI presents the classification performance of the proposed methodology in all the test cases with different values of nearest neighbor and it is examined that KNN classifier with K=10 has better overall classification performance results as compared to K=3.

TABLE 5. The performance classification of different sets of EEG data using SVM classifier with RBF kernel function and polynomial kernel function.

Data Group	SVM with RBF kernel function			SVM with polynomial kernel function		
	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Set A vs Set E	100	100	100	100	100	100
Set B vs Set E	99.46	93.86	96.5	99.47	95.21	97.25
Set C vs Set E	98.5	98.5	98.5	98	98.49	98.25
Set D vs Set E	90.95	95.26	93	90.6	96.25	93.25

TABLE 6. The performance classification of different sets of EEG data using KNN with K=3 and K=10.

Data Group	KNN(K=3)			KNN (K=10)		
	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Set A vs Set E	100	100	100	100	100	100
Set B vs Set E	98.90	95.19	93	97.3	91.16	94.25
Set C vs Set E	96.5	96.5	96.5	97.05	98.97	98
Set D vs Set E	90.68	92.34	91.5	91.26	93.81	92.5

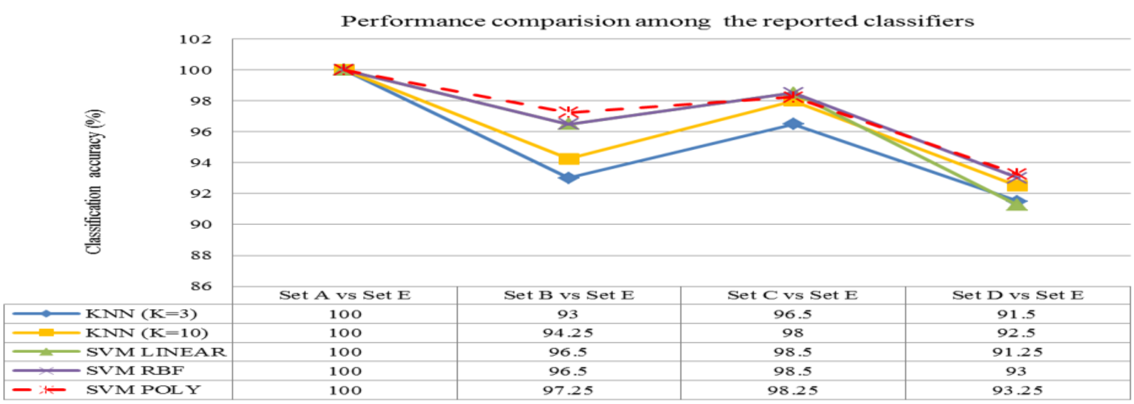

FIGURE 10. Performance comparison of the reported classifiers in term of overall accuracy.

Fig. 10 illustrates the comparative analysis of the classification accuracy of the proposed technique on all the four test cases with different classifiers that are applied in the above experiments. According to the classification results shown in the Fig.10, it is clearly observing that for all of the experimental classifier used in this paper, the accuracy result is very close to each other.

Even though the SVM classifier with linear and RBF kernel functions shows the same accuracy value, i.e. 96.5% for the test case II and 98.5% of the test case III. In addition, it is examined that the proposed technique is 100% efficient to discriminate between EEG signals of seizure and healthy patient with eyes open. The overall classification performance, i.e. sensitivity, specificity and accuracy with combined feature vector sets for test case I is 100% with all different classifiers which is clearly demonstrated by all of the above classification experimentation tables. It is also observed that this proposed methodology achieves higher experimental results for all test cases.

Moreover, Fig. 10 also represent that SVM with polynomial kernel function accomplish the highest accuracy as compared to other classifiers therefore it is best suitable when using these two statistical properties as combined features. Fig. 11 represent 100% performance accuracy of set E vs set A by combining two feature vector sets via using (a) SVM classifier with linear kernel function, (b) SVM classifier with RBF kernel function, (c) SVM classifier with polynomial function, (d) KNN classifier with K=3, (e) KNN classifier with K=10 with 1024 data samples per segment, where training group 1 signifies seizure activity and training group 2 mean EEG data of healthy patients with eyes open.

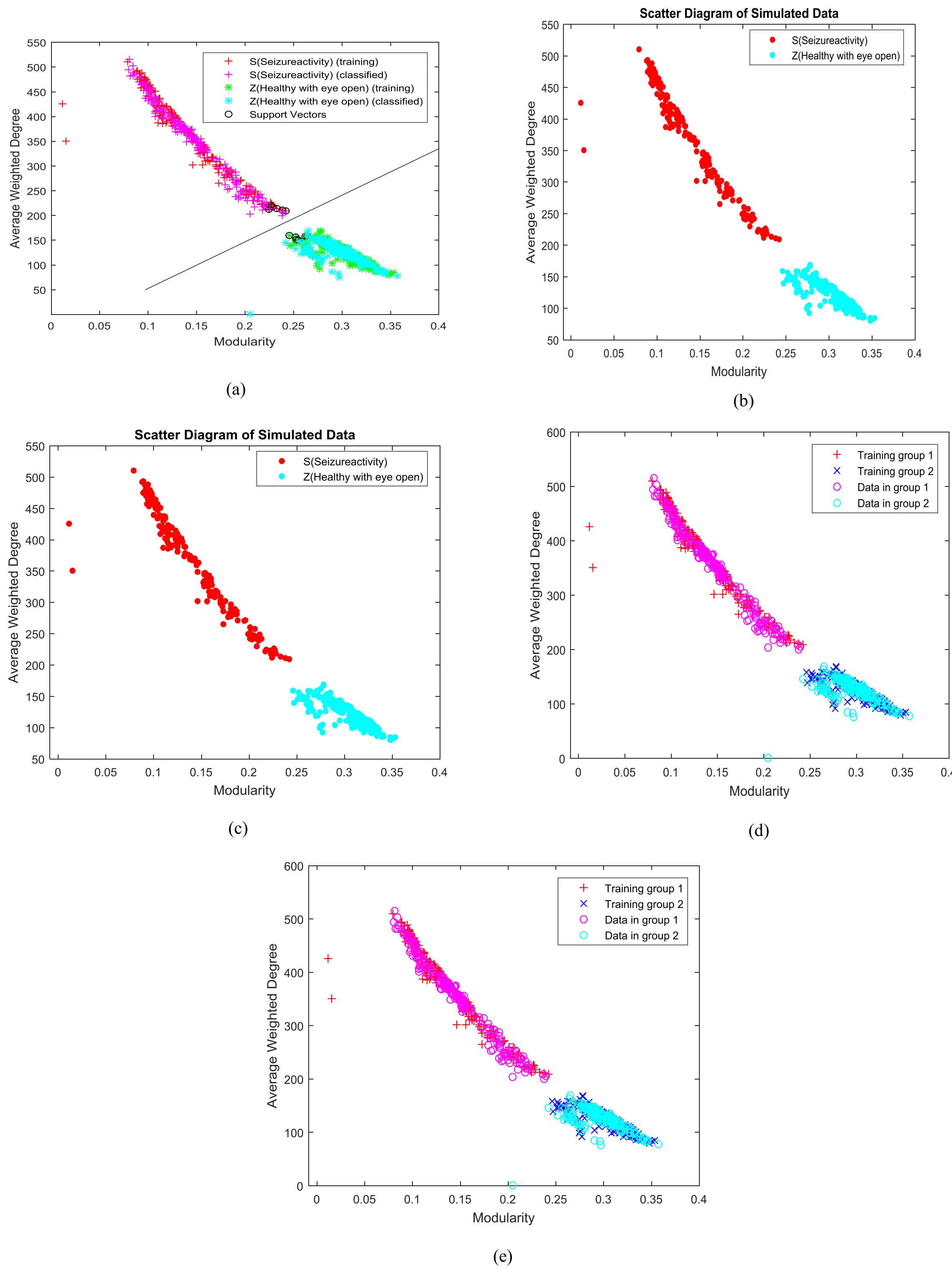

FIGURE 11. Illustration of classification accuracy for set A vs set E by combining two features and using classifier (a) SVM with linear kernel, (b) SVM with RBF kernel, (c) SVM classifier with polynomial, (d) KNN with K=3, (e) KNN with K=10.

Table VII presents the comparative analysis of the classification accuracy of the proposed method with different methods in the literature that perform experimentation on the same EEG data set and illustrate that the proposed methodology is more accurate for detection of epileptic seizure as compared to them.

Finally, the above analysis results reveal that the combination of these two features (modularity and average weighted

TABLE 7. Comparative analysis of the accuracy of the proposed work with existing work that used the same data set for their experimentation.

Data Set	Authors	Features	Accuracy (%)
A vs E	Srinivasan et al.,2005[12]	5	99.6
	Siuly et al. ,2011[31]	9	99.9
	Nicolaou et al., 2012[32]	1	93.42
	Guohun Zhu et al., 2014 [19]	2	99.0
	Ghayab et al., 2016[34]	9	99.90
	S. Husain et al.,2014[35]	-	99.8
	Our proposed technique	2	100
B vs E	Siuly et al. ,2011[31]	9	93.6
	Guohun Zhu et al., 2014 [19]	2	97.0
	Our proposed technique	2	97.25
C vs E	Guohun Zhu et al., 2014 [19]	2	98.0
	Siuly et al. ,2011[31]	9	96.20
	Our proposed technique	2	98.25
D vs E	Y.Kumar et al.,2014[33]	-	93
	Siuly et al. ,2011[31]	9	93.60
	Guohun Zhu et al., 2014 [19]	2	93
	Nicolaou et al., 2012[32]	1	83.13
	Our proposed technique	2	93.25

degree) of the complex network is very useful to characterize the underlying dynamics of different EEG signals with different brain conditions. This paper investigates that as ictal EEG signals (set E) are more chaotic in nature and therefore it is difficult to divide it into different clusters (communities) and this is the main reason why the modularity feature set of ictal EEG has the lowest value as compared to other EEG data sets. This work can be enhanced for detection of other brain disorders. The data sample points per segments can be varied according to the requirement. This novel technique can also be applicable to other time series data. Moreover, in future this proposed technique can be used with WSN-based healthcare applications [36] to make available high-quality medical services. It is our believe that this proposed methodology will support the technicians to build a software system that will provide support for automatic detection of epileptic seizure and also will help the expert neurologist to identify epileptic signals and collect valuable information about the brain state which will further aid for improving the diagnosis of epilepsy from EEG signals.

IV. CONCLUSION

In this paper, we introduce a novel technique to detect epileptic seizure activity from brain EEG signals considering modularity and average weighted degree features with edge weight in the natural visibility graph. In the proposed methodology, firstly the EEG time series data are converted into a weighted visibility graph (WVG). Then the modularity and average weighted degree are extracted from the WVG as features and after that, the features are tested by employing two popular machine learning methods: SVM and KNN classifiers. In this study, the SVM classifier was assessed with three kernel function (e.g. Linear kernel, RBF kernel and polynomial kernel) and an optimum parameter value for k were obtained after an empirical evaluation. Then the classification performance of the proposed methodology was measured on several groups of EEG signals such as, Set A vs Set E, Set B vs Set E, Set C vs Set E, and Set D vs Set E and achieved promising results. Moreover the classification performance results (i.e. sensitivity, specificity and accuracy) for ictal (set E) and normal healthy person EEG (set A) is achieved by100%. This study explores that EEG signals can be best described by weighted network for detection of epilepsy as the nodes interact with each other with varying strength. It is also investigated that due to the chaotic nature of ictal EEG data it is difficult to divide it into different modules. Hence the results in small values of modularity feature and large value for average weighted degree features were compared to other EEG signals. The pilot study in this paper, has examined that the proposed methodology is best suitable to discriminate between two different EEG signals. This work can be enhanced to real-time detection of epilepsy disorder. We are currently planning to extend this proposed methodology to detect other brain disorders through EEG, such as, Alzheimer's disease, autism, dementia and also in the field of motor imagery EEG data and mental imagery task EEG data.

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